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BULBOUS BOW SHAPE OPTIMIZATION

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Abstract. The aim of this study is to prove the usefulness of a bulbous bow for a fishing vessel, in terms of drag reduction, using an automated shape optimization procedure including hydrodynamic simulations. A bulbous bow is an appendage that is known to reduce the drag, thanks to its influence on the bow wave system. However, the definition of the geometrical parameters of the bulb, such as its length and thickness, is not intuitive, as both parameters are coupled with regards to their influence on the final drag. Therefore, we propose to use an automated shape optimization procedure, based on a high-fidelity flow solver, a surrogate model-based optimizer and a CAD-based geometrical model, to derive the characteristics of the bow geometry allowing to maximize the achievable drag reduction. The numerical tools are first presented, and then applied to the optimization of a bow shape for a real fishing vessel, in order to determine the optimal length and thickness of the bow for drag reduction purpose.

1 INTRODUCTION

Simulation-based design optimization procedures are of growing interest in naval engineering, since CFD (Computation Fluid Dynamics) simulations are now reliable and this approach allows to obtain a significant performance improvement for a moderate cost, in comparison with experimental campaigns using towing tank facilities. Moreover, the optimization is based on a rigorous mathematical framework that can outclass the intuition and propose original design solutions.

To solve realistic problems, the design procedure should include several software components, such as a geometrical modeler, a grid generator, a flow solver and a design optimizer, each of them relying on complex numerical methods. Because of the computational costs related to high-fidelity simulations (unsteady turbulent flows with free-surface capturing), the efficiency of the overall procedure is a critical aspect for application to real-life problems.

In the present study, we present some recent numerical developments, originating from academic and industrial fields, to overcome the different issues that arise when solving realistic problems. In particular, we describe how the computational grid is generated automatically from a reduced set of parameters, via a CAD-based (Computer-Aided Design) model. We also make a focus on the use of surrogate models in this complex context. The optimization of a bulbous bow for a real fishing vessel is considered as test-case.

2 DESIGN PROCEDURE

The design optimization procedure gathers different software components: the *CAD modeler* in charge of constructing a geometrical hull model from a set of design parameters, the *grid generator* in charge of building the computational domain in accordance with the geometry, the *flow solver* in charge of computing the ship performance and finally the *optimizer* in charge of providing a new set of parameters according to the past simulations.

The optimization algorithm used for this study relies on the construction of a surrogate Gaussian model, that is used to derive new sets of design parameters at each iteration. Then, the evaluation of the performance values associated to these sets can be achieved independently, in a parallel way. The overall procedure is described schematically by Figure 1.

3 NUMERICAL METHODS

3.1 Hull geometric model

The construction of the geometrical model for design optimization purpose is a difficult task, since it has to fulfill several criteria, sometimes antagonistic. Firstly, the shape of interest should be precisely defined, but at the same time one would like to modify it with a few number of design parameters to facilitate the optimizer task. Secondly, a high regularity and accuracy is required to allow the fluid mesh generation, while some sharp edges should be maintained. Moreover, large deformations should be permitted, and the

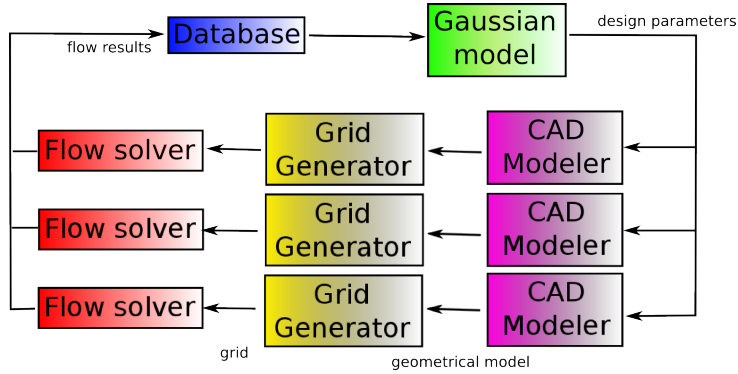


Figure 1: Overview of surrogate model-based optimization procedure.

final optimized shape should be compliant with respect a classical CAD systems, to allow a manufacturing process.

To try to fulfill most of these criteria, the construction of the geometric model is achieved with the help of the CAD platform AXEL, developed at INRIA by Galaad Project-Team (<http://axel.inria.fr>). The baseline geometry of the fishing vessel without bow is imported in IGES format, yielding the definition of the geometry as a set of cubic NURBS patches, as illustrated by Figure 2. The white dots represent the NURBS control points.

To generate the bow shape, a restricted patch is defined by cutting the baseline patch along constant parameter curves, in blue on Figure 2. then, its control points can be moved to create the desired shape. Finally, the two patches are merged back into a single NURBS patch, which allows to ensure a C^2 surface regularity at the junction between the bow and the hull, as illustrated by Figure 2.

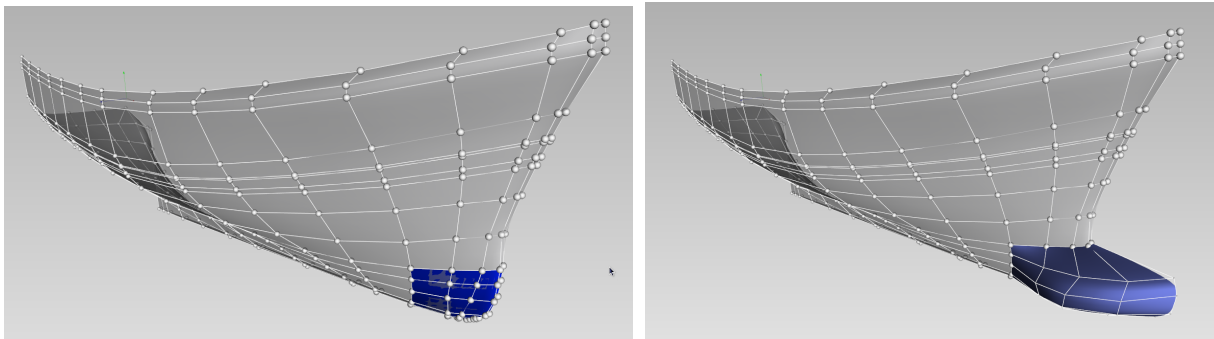


Figure 2: Baseline (left) and deformed (right) geometrical model.

This bow shape is obtained by moving approximately 20 control points, yielding a bow defined by 60 design variables. In the perspective of design optimization, the shape

definition has to be reduced to a smaller set of meaningful parameters, which avoid the generation of non-realistic bows. Therefore, a two-step approach is adopted: a baseline deformation is first defined by moving the control points, in order to generate a nearly cylindrical bow shape. In a second step, a family of bows is generated by applying some homothetic transformations, according to only two parameters: the bow length and thickness. Figure 3 shows some representatives of this family, that correspond to different length and thickness parameters. Finally, these two parameters are chosen as optimization variables for the forthcoming study.

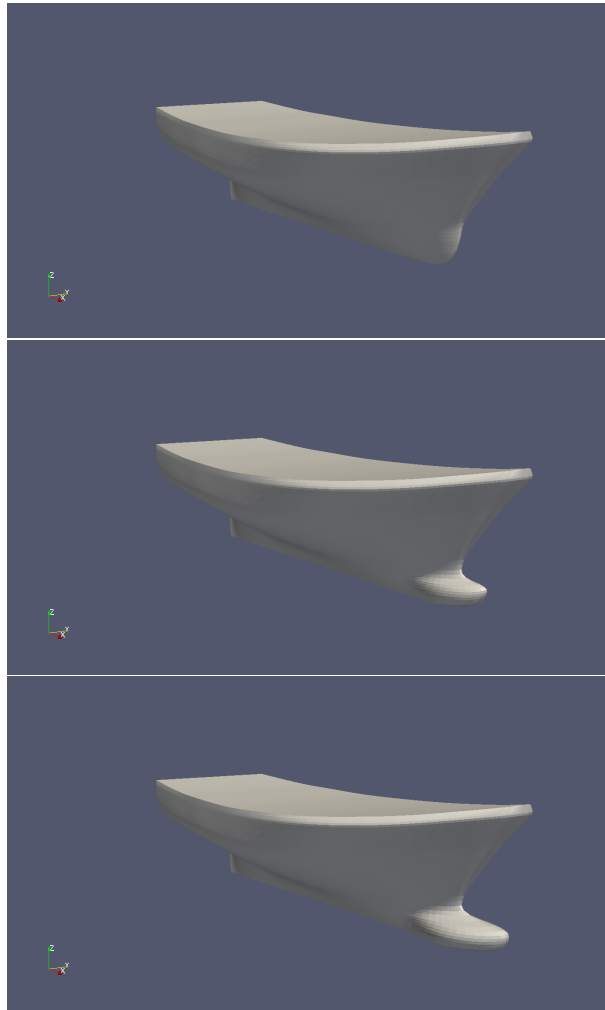


Figure 3: Some representatives of the generated hull shapes.

3.2 Mesh generation

To generate the computational grid, a closed water-tight triangularized volume, embedding the ship hull, should be generated. This task is carried out by defining additional NURBS patches on the plane surfaces limiting the computational domain and then discretizing all the patches along constant parameter values.

An body-fitted computational grid is then built using the software HEXPRESSTM from Numeca International. HEXPRESSTM generates non-conformal full hexahedral unstructured meshes on complex arbitrary geometries. In addition, the advanced smoothing capability provides high-quality boundary layers insertion [6, 7]. One of the meshes of our study case is illustrated by Figure 4. The grid generation process requires closed geometries to provide robust meshes. During the triangulation generation, a nonconforming mesh is produced, leading to the appearance of holes in the geometry. Therefore, the computational grid required human intervention in order to force HEXPRESSTM to correct these discontinuities in the mesh. For some large bow deformations, involving large triangulation deformation, the computational grid could not be generated.

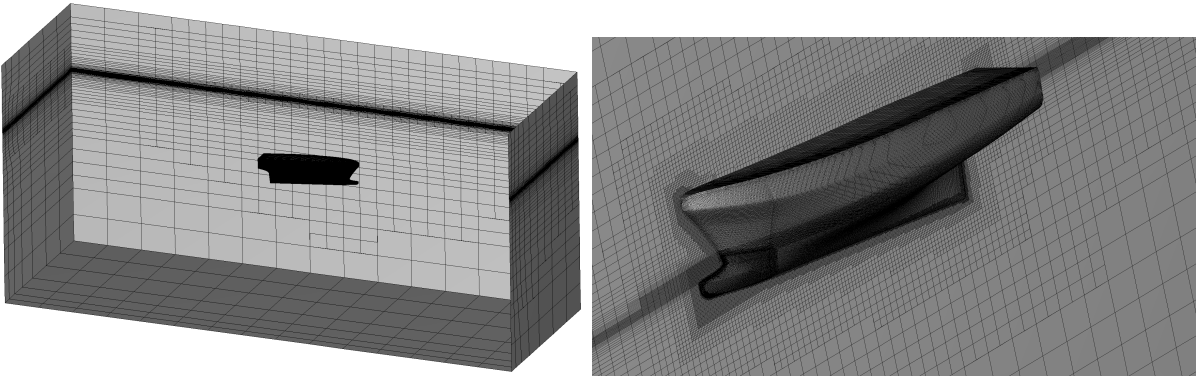


Figure 4: Some generated meshes of hull.

During the computation, the automatic mesh refinement feature has been used. Automatic, adaptive mesh refinement is a technique for optimising the grid in the simulation, by adapting the grid to the flow as it develops during the simulation. This is done by locally dividing cells into smaller cells, or if necessary, by merging small cells back into larger cells in order to undo earlier refinement. During the computation, the number of cells increases from 3 to 3.6 million cells.

3.3 Flow simulation

ISIS-CFD, available as a part of the FINETM/Marine computing suite, is an incompressible, unsteady Reynolds-averaged Navier-Stokes (RANS) solver [3, 4]. The solver is based on the finite volume method to build the spatial discretisation of the transport

equations. The unstructured discretisation is face-based, which means that cells with an arbitrary number of arbitrarily shaped faces are accepted. This makes the solver ideal for adaptive grid refinement, as it can perform computations on locally refined grids without any modification.

Free-surface flow is simulated with a multi-phase flow approach: the water surface is captured with a conservation equation for the volume fraction of water, discretised with specific compressive discretisation schemes [4]. Furthermore, the method features sophisticated turbulence models [3] and 6 DOF (Degree Of Freedom) motion simulation for free moving ships [5]. In our case, only 2 DOF are used. Post-processing for our test-case illustrates the simulation of the free surface motion on Figure 5.

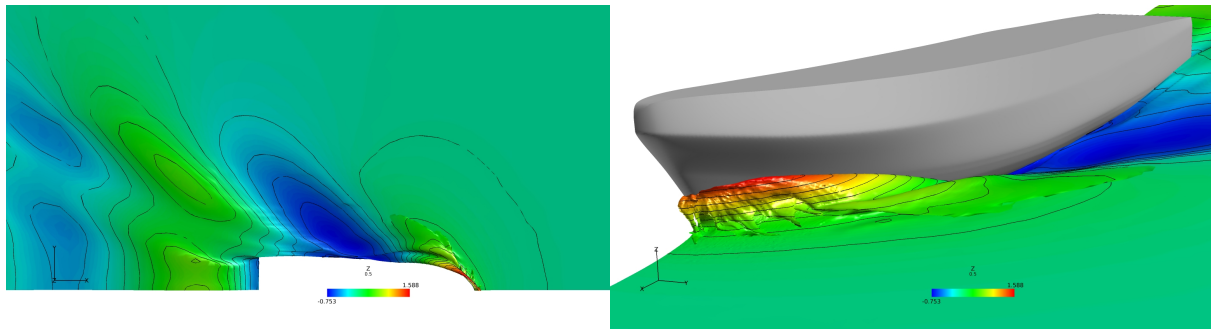


Figure 5: Post-processing of the ISIS-CFD™ computation

3.4 Optimization

When dealing with three-dimensional turbulent flows, possibly unsteady flows, the main issue for the purpose of optimization is the computational burden. The evaluation of the objective function gradient using an adjoint approach is highly complex and the non-linearities underlying phenomena may generate multimodal objective functions exhibiting several local optima. Furthermore, simulation errors due to spatial and temporal discretization, partial convergence, etc, make the evaluations noisy. To address all these issues, the use of a surrogate model-based algorithm is adopted in the present study. In particular, this work is focused on the Efficient Global Optimization (EGO) algorithm.

The Efficient Global Optimization (EGO) is a global optimization algorithm that makes use of a stochastic surrogate model to drive the optimization [1]. One may be wondering about using a stochastic model, although the system is fully deterministic. This is justified by the fact that the model is constructed on the basis of a finite number of observations. The resulting uncertainty is modeled in a stochastic framework.

The algorithm starts from a Design of Experiments (DOE) phase: A database exploring the bounded search space is generated from simulation results. This database contains the objective function values, each of them being associated to a set of design parameters. In

a second phase, a Gaussian process model is constructed using this database, which allows the prediction of both the objective function value and an estimated model uncertainty at any point of the search domain. According to these predictions, the most interesting points are selected by means of a merit function. Usually, one selects the points that maximize the Probability of Improvement (PI) or the Expected Improvement (EI) merit function. Once evaluated, the corresponding objective function values are added to the database. This process is repeated until convergence, as illustrated on Fig. 1. A detailed description of the model construction and the merit function treatment can be found in [2]. The algorithm is part of the FAMOSA platform, developed at INRIA by Opale Project-Team.

4 APPLICATION TO A FISHING VESSEL

4.1 Initial fishing vessel without bow

The hull studied is an existing fishing vessel. Its main characteristics are :

- Boat speed : 6.687 m/s (12 nds)
- Length : 22m
- Center of gravity : (10.42, 0, -0.75)
- Displacement : 150 Tons

Simulation set up is the following :

Fluid characteristics		
	$\rho(kg/m^3)$	$\mu(Pa.s)$
Water	1025	$1.07 * 10^{-3}$
Air	1.2	$1.85 * 10^{-5}$

Fluid domain		
	min	max
X	-62	+61
Y	-41	0
Z	-41	+16

- Froude number 0.45
- Reynolds number $1.4 * 10^8$
- Turbulence model : SST $k - \omega$
- Motion : trim and sinkage solved
- Motion : imposed speed according to a half sinusoidal ramp law from 0 m/s to 6.687 m/s in 12 seconds

The reference drag computed for the initial half-hull without bow is $-7.4829 * 10^4 N$

4.2 Design of experiments

As explained above, the first phase of the design procedure consists in exploring the design space using a DOE approach. Therefore, two admissible intervals are defined for the two selected design parameters (length l and thickness t), such as $1.4 < l < 2.8$ and $0.0 < t < 1.4$, and a distribution of design points is generated. A first set of points, corresponding to moderate bow dimensions, is created according to a Latin Hypercube Sampling (LHS). Additional points are then added to explore the possibility of larger deformations. Figure 6 shows the 22 design points in the parameter space.

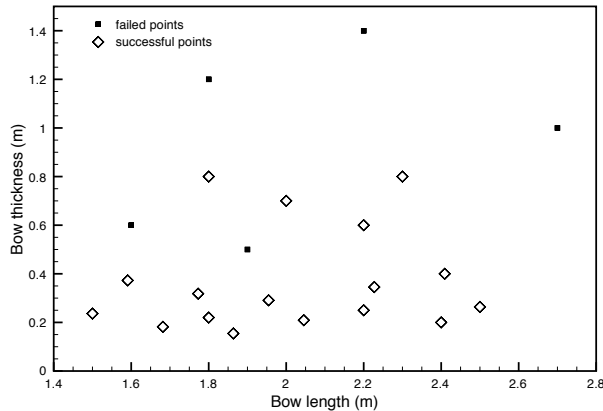


Figure 6: Design of experiments.

The evaluation of the performance corresponding to these points shows that about 20% of the evaluations fails, especially for large bow deformations (grid generation failures). Therefore, the forthcoming study is restricted to mild shape deformation $l < 2.5$ and $t < 0.8$.

4.3 Optimization of length and thickness

A Gaussian surrogate model is constructed on the basis of the successful evaluations. A major difficulty arises here, due to the fact that the estimated resistance values are very close to each other. Actually, the variation of the total resistance observed over the computed set is about 5%, which is nearly the accuracy of the resistance prediction. Since the surrogate model construction permits to take into account some uncertainty on the evaluations (noisy observations), a range of models is built, from an interpolating model which supposes that the evaluations are exact, to models based on a prescribed error value, in terms of standard deviation. The three models are depicted in Figure 7.

The interpolating model exhibits some oscillations and several interesting areas. In particular, the most efficient bow shapes are found either for a long and thin bulb ($l \simeq 2.0$ and $t \simeq 0.2$), or for a longer and bulky bulb ($l \simeq 2.3$ and $t \simeq 0.8$), as shown in Figure 9.

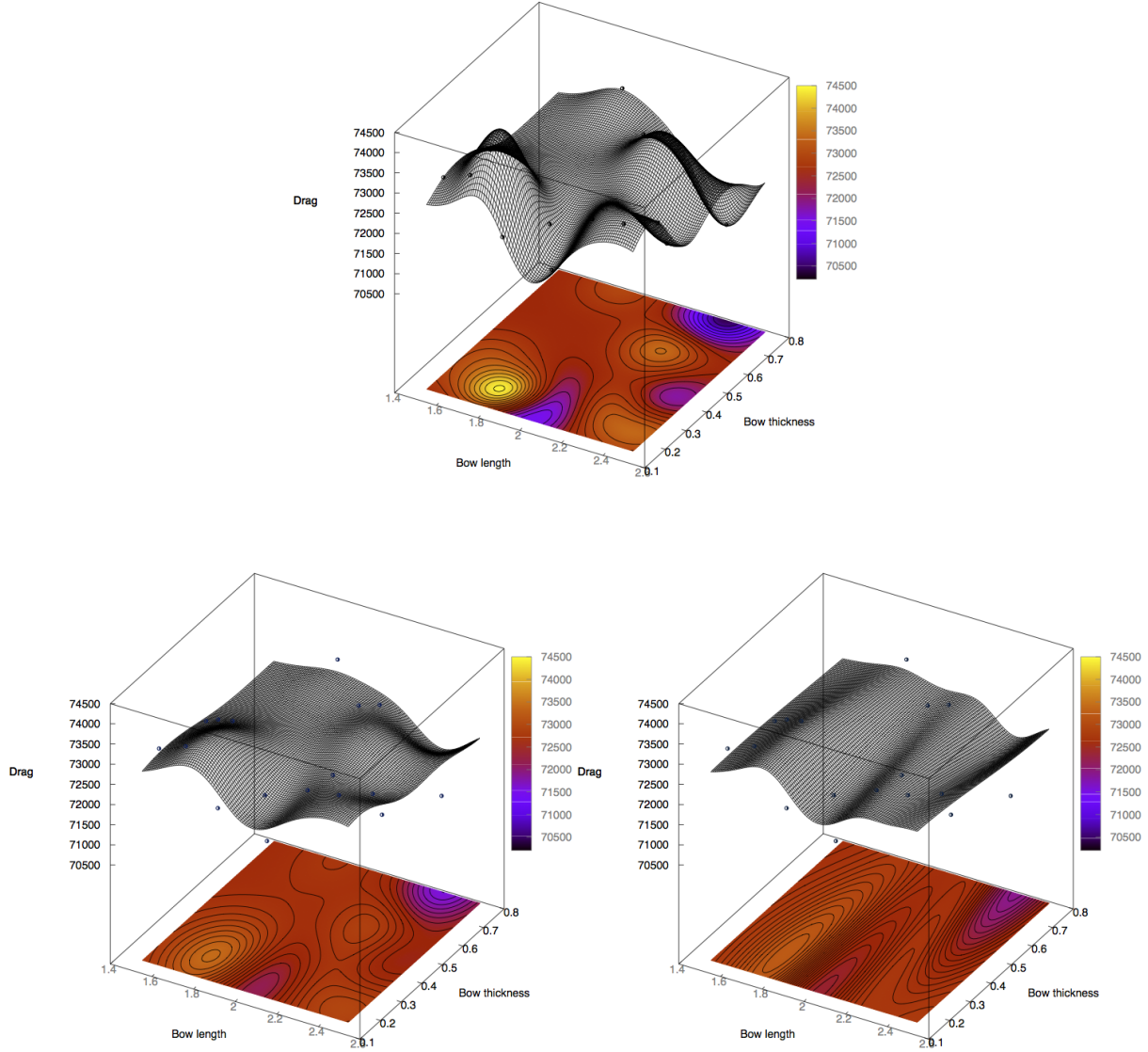


Figure 7: Surrogate model without error (top), with 1% error (left) and 2% error (right).

Unfortunately, the best design point found (6% drag reduction with respect to the original fishing vessel) is located on the boundary of the search domain. One should notice that all tested bows improve the estimated performance.

When a rather small evaluation error is taken into account, the model quickly becomes flat, which indicates that the numerical error plays a critical role here and it is difficult to identify a clear trend with the current set of evaluations. Nevertheless, the two interesting

regions already identified remain, even if their extent is not so obvious.

If one determines the design point that maximizes the Expected Improvement criterion, the first two models agree to select a point on the right boundary of the domain ($l \simeq 2.5$ and $t \simeq 0.5$), in black on Figure 9. For the last model, the flat behavior yields a point almost equal to the best point found so far, at the top right-hand corner of the domain.

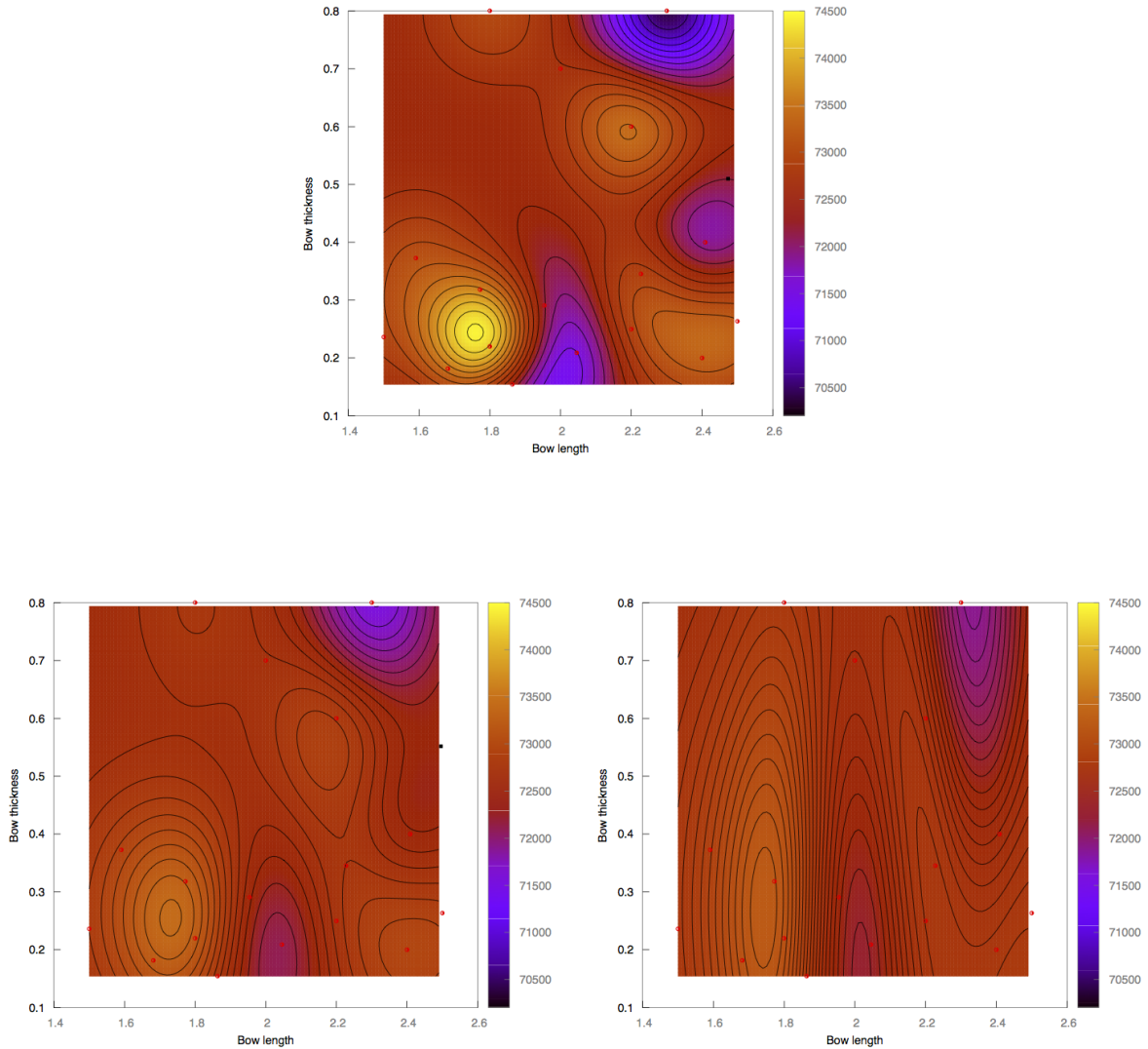


Figure 8: Performance map without error (top), with 1% error (left) and 2% error (right).

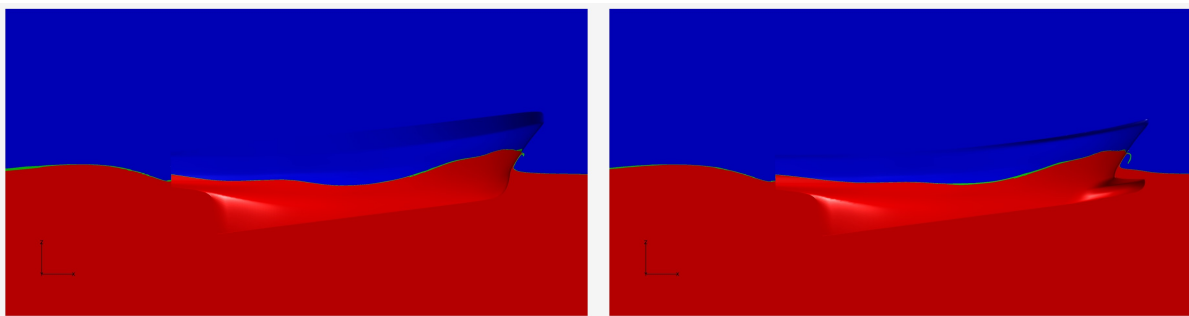


Figure 9: Reference Bulb and actual best bulb.

5 CONCLUSIONS

A design optimization procedure, based on a high-fidelity CFD analysis tool has been developed and applied to a realistic problem, dealing with the optimization of the bow shape of a fishing vessel. The difficulty to automatically generate a suitable computational grid from any set of design parameters has been reported, and has unfortunately restricted the admissible interval of design parameters. Another difficulty related to the construction of surrogate models in the presence of numerical errors arising from the simulation has also been pointed out.

Nevertheless, this study demonstrates that it is now possible to construct a design optimization loop based on sophisticated numerical tools in naval engineering context and apply it to real life problems. Forthcoming developments will extend the current methods and results.

6 ACKNOWLEDGEMENT

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